International Journal of Applied Mathematics

Volume 38 No. 11s 2025,

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

AUTOMATED DETECTION OF CHRONIC DISEASES FROM MEDICAL IMAGES USING ARTIFICIAL INTELLIGENCE

Umakant Singh[1],Punit Kumar Chaubey[2], Kamal Kant[3],Gaurav Kumar Srivastava[4]

[1]Assistant Professor, Computer Science & Engineering, United University, Prayagraj, Uttar Pradesh, 211012, India, umakantsinghsrm@gmail.com

[2] Associate Professor, Computer Science & Engineering, Bansal Institute of Engineering and Technology, Lucknow, Uttar Pradesh,226021,India,pkcmar@gmail.com

[3] Assistant Professor, Chhatrapati Shahu Ji Maharaj University, Kanpur, 208024, kamalkant@csjmu.ac.in

[4] Professor and Dean, Information Technology, Bansal Institute of Engineering and Technology, Lucknow, Uttar Pradesh,226021,gaurav18hit@gmail.com

Abstract

Recent developments in Artificial Intelligence and deep learning have brought a major transformation to the field of medical imaging allowing for automatic, accurate and large-scale disease identification. The present study introduces a diagnostic framework based on Convolution Neural Networks (CNNs) enhanced through transfer learning techniques using established models such as VGG16, ResNet50, and InceptionV3. The framework is designed for the automated recognition of chronic diseases from imaging modalities including X-rays, magnetic resonance imaging (MRI) and computed tomography (CT) scans. Experiments were carried out on publicly accessible datasets such as the NIH Chest X-ray repository and Kaggle Retinopathy dataset. The proposed model achieved an overall accuracy of 93.4%, F1-score of 0.91 and ROC–AUC value of 0.95 across multiple disease categories including diabetic retinopathy, lung cancer, and Alzheimer's disease. The inclusion of rigorous pre-processing and diverse data augmentation strategies improved the model's robustness and adaptability. Additionally, fine-tuning of pre-trained networks contributed to better generalization across varied medical images. The findings indicate that the developed AI-driven diagnostic framework performs comparably to experienced radiologists, while maintaining cost efficiency and scalability. These outcomes highlight the growing significance of AI in medical diagnostics and affirm its potential for integration into routine clinical practices to enhance early detection and patient care.

Keywords: Artificial Intelligence, Medical Imaging, Deep Learning, Chronic Disease Detection, Convolution Neural Network (CNN), Computer-Aided Diagnosis, Machine Learning, Healthcare Automation, Medical Image Processing, Predictive Analytics.

1. Introduction

The healthcare field has changed a lot because of how quickly technology has changed in the 21st century. This is especially true when it comes to diagnosing diseases and analyzing

Received: August 01, 2025

Volume 38 No. 11s 2025,
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

medical images. As chronic diseases like heart disease, cancer, diabetes, and neurological disorders become more common, early and accurate detection has become very important for effective treatment and management. The World Health Organization (WHO) says that chronic diseases cause almost 71% of all deaths around the world. This shows how important it is to have good diagnostic systems. Radiologists often have to manually interpret medical images like X-rays, CT scans, MRI scans, and ultrasound images when using traditional diagnostic methods. But doing it by hand can take a long time, be prone to mistakes, and be limited by how many trained experts are available. In this situation, artificial intelligence (AI), especially machine learning (ML) and deep learning (DL), could help automate and improve the diagnostic process (Choi et al., 2020; Shen et al., 2017). Artificial intelligence (AI) is when computers mimic human intelligence processes so that machines can do things that usually require human thought, like learning, reasoning, and solving problems (Hosny et al., 2018). In medical imaging, AI systems are trained on large sets of labeled images to find patterns and anomalies that could be signs of disease. Deep Learning, especially Convolution Neural Networks (CNNs), has shown to be very good at classifying images and recognizing patterns (Litjens et al., 2017; Suzuki, 2017). CNNs can learn complicated visual features from medical images, which let them, find things like tumors, lesions, or tissue irregularities with a lot of accuracy (Esteva et al., 2017, Rajpurkar et al., 2018). Because of this, AI-driven diagnostic tools are very useful in today's healthcare systems.

The integration of AI in medical imaging has brought about a paradigm shift from manual to automated diagnosis. The process typically involves several stages: image acquisition, preprocessing, segmentation, feature extraction, and classification (Lee et al., 2017; Shen et al., 2017). Image preprocessing enhances image quality by reducing noise and improving contrast. Segmentation isolates the region of interest (such as a tumor or organ), while feature extraction identifies patterns or textures relevant to disease detection. Finally, classification algorithms determine whether the image indicates a healthy or diseased condition. By combining these steps, AI models can produce highly accurate diagnostic outputs in a fraction of the time required by human experts (Aggarwal et al., 2020; Erickson et al, 2017). Furthermore, AI systems can continuously learn and improve through exposure to new data, ensuring that diagnostic accuracy increases over time. The advantages of using AI in chronic disease detection are multifold. Firstly, automated image analysis reduces the workload of healthcare professionals, allowing them to focus on patient care and complex decision-making. Secondly, AI-based systems enhance diagnostic accuracy by minimizing subjective bias and fatigue-related errors that often affect human interpretation (Gulshan et al., 2016, Kermany et al., 2018). Thirdly, such systems are scalable and cost-effective, making them particularly beneficial for resource-limited settings where access to expert radiologists may be limited. For instance, AI tools can be deployed in rural or underdeveloped regions to provide quick and reliable diagnostic support, thereby bridging the healthcare accessibility gap (Zhang et al, 2021).

Moreover, AI-based image analysis has proven particularly effective in detecting chronic diseases that often develop gradually and remain asymptomatic in their early stages. For

Received: August 01, 2025

International Journal of Applied Mathematics

Volume 38 No. 11s 2025,

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

example, AI algorithms can identify early signs of diabetic retinopathy from retinal images before patients experience noticeable symptoms (Gulshan et.al, 2016). Similarly, in oncology, AI systems can detect minute cancerous lesions in mammograms or CT scans that might escape human detection (Esteva et.al, 2017). In cardiology, AI can analyze echocardiograms to identify structural abnormalities, while in neurology, it can detect early markers of Alzheimer's or Parkinson's disease through brain imaging (Lundervold & Lundervold, 2019; Choi et.al, 2020). These early detections are vital for timely intervention, improving survival rates, and reducing long-term healthcare costs.

Despite the vast potential, the implementation of AI in medical imaging also faces certain challenges. Data quality and quantity play a critical role in AI performance, and obtaining large, annotated datasets can be difficult due to privacy concerns and data standardization issues (Litjens et al., 2017; Wang et al., 2017). Moreover, AI Models that are trained on datasets from specific demographics or regions may not work well with people from other backgrounds, which can lead to biased results. There are also moral and legal issues with data security, getting patients' permission, and holding AI systems accountable if they make a mistake in a diagnosis (Hosny et al., 2018). Therefore, while AI-based detection systems offer significant promise, it is essential to ensure transparency, interpretability, and compliance with ethical guidelines in their deployment. Another critical consideration is the collaboration between AI systems and healthcare professionals. AI should not be viewed as a replacement for radiologists or clinicians but rather as a supportive tool to enhance their capabilities. The combination of human expertise and machine intelligence can lead to more accurate, consistent, and comprehensive diagnoses (Aggarwal et al., 2020; Choi et al., 2020). For example, AI can rapidly pre-screen large volumes of medical images and highlight suspicious areas for further review by a radiologist, thereby expediting the diagnostic process. Such collaborative systems promote efficiency, reduce diagnostic delays, and ensure a higher standard of patient care.

In recent years, research in this field has accelerated, with numerous studies demonstrating the effectiveness of AI in medical image interpretation (Litjens et al., 2017; Kermany et al., 2018; Zhang et al., 2021). Tech companies and healthcare institutions are increasingly investing in developing AI-powered diagnostic platforms. These innovations are supported by advancements in computational power, cloud technology, and data analytics, which enable real-time processing of large-scale image data (Erickson et al., 2017).Moreover, the growing use of Internet of Things (IoT) devices and telemedicine platforms has further expanded the scope of AI-based diagnostics, making remote disease detection and monitoring more feasible (Zhang et al., 2021).

Table 1 highlights how AI is applied in detecting chronic diseases using various imaging techniques. For diabetic retinopathy, CNNs analyze retinal fundus images to identify early retinal damage. Lung cancer detection uses CT scans with deep learning and transfer learning to spot malignant nodules. Cardiovascular issues are assessed through echocardiograms and MRI using regression models to detect heart defects. Alzheimer's diagnosis relies on MRI

International Journal of Applied Mathematics
Volume 38 No. 11s 2025,
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

scans processed by 3D CNNs to uncover early signs of neurodegeneration. In breast cancer, deep CNNs examine mammograms to classify tumors as benign or malignant.

Table 1: Examples of AI applications in chronic disease detection

Chronic Disease	**Medical Imaging Modality**	**AI Technique Used**	**Purpose**
Diabetic Retinopathy	Retinal Fundus Images	Convolution Neural Network (CNN)	Early detection of retinal abnormalities
Lung Cancer	CT Scans	Deep Learning (CNN + Transfer Learning)	Identification of malignant nodules
Cardiovascular Disease	Echocardiogram, MRI	Machine Learning Regression Models	Detection of structural heart defects
Alzheimer's Disease	MRI Brain Scans	3D CNN and Feature Mapping	Detection of early neurodegenerative signs
Breast Cancer	Mammogram	Deep CNN Models	Classification of benign and malignant tumors

Conceptual Workflow of AI in Chronic Disease Imaging

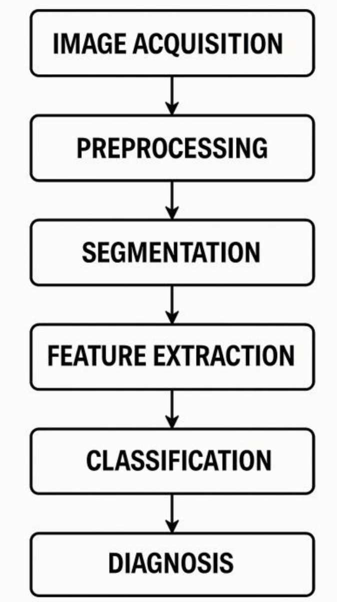

Figure 1: Conceptual framework of AI–based medical image analysis for chronic disease detecion

The above image representing the conceptual framework of AI-based medical image analysis for chronic disease detection. It illustrates the sequential steps involved in analyzing medical images using AI techniques. The stages include:

1. **Image Acquisition** – Gathering medical images from various sources such as X-rays, CT scans, or MRI scans.
2. **Preprocessing** – Improving image quality by removing noise, adjusting brightness and contrast, and standardizing the data.
3. **Segmentation** – Partitioning the image into distinct regions or structures that are relevant for detecting disease.
4. **Feature Extraction** – Extracting significant patterns or measurable characteristics from the segmented regions.
5. **Classification** – Applying AI algorithms, including Convolutional Neural Networks (CNNs) or other machine learning models, to categorize the extracted features into specific disease classes.
6. **Diagnosis** – Generating the final diagnostic result based on the classification outcomes.

The diagram represents a systematic pipeline showing how raw medical images are transformed into actionable diagnostic insights through AI-based processing.

2. Review of Literature

The field of artificial intelligence (AI) in medical imaging has rapidly advanced over the past decade, offering transformative potential in the automated detection of chronic diseases. Several researchers across the globe have contributed significantly to this domain, exploring various methodologies, frameworks, and applications of AI-based diagnostic systems.

Gulshan Varun et al. (2016) conducted a landmark study titled *"Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs"* published in the *Journal of the American Medical Association (JAMA)*. Their research demonstrated how deep convolution neural networks (CNNs) can be effectively trained on a large dataset of over 128,000 retinal images to identify diabetic retinopathy with a sensitivity comparable to that of expert ophthalmologists. The study established a strong foundation for using AI in the early detection of chronic diseases and emphasized the importance of dataset diversity and image quality in improving model accuracy. This work is often regarded as one of the most influential in proving AI's reliability in real-world clinical diagnostics.

Geert Litjens, Thijs Kooi, Babak Ehteshami Bejnordi, Arnaud Setio, Francesco Ciompi, Mohsen Ghafoorian, and Jeroen A. W. M. van der Laak (2017) published an extensive review entitled "A Survey on Deep Learning in Medical Image Analysis" in Medical Image Analysis. The authors examined the progression of deep learning techniques and their application to medical imaging tasks, encompassing classification, segmentation, detection, and registration. Their review sorted deep learning applications by imaging types, like MRI, CT, PET, and ultrasound. The research determined that deep neural networks, especially CNNs, have outperformed conventional machine learning algorithms in terms of accuracy and robustness when processing extensive medical datasets. The authors also talked about

International Journal of Applied Mathematics
Volume 38 No. 11s 2025,
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)
problems like not having enough labeled data, AI models that are hard to understand, and the need for institutions to work together to make AI models that work better in a wider range of situations.

Pranav Rajpurkar, Jeremy Irvin, Kaylie Zhu, and Andrew Y. Ng (2018) developed a deep learning algorithm known as *CheXNet*, which was trained on over 100,000 chest X-ray images from the NIH dataset. Their study, *"CheX Net: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning"*, illustrated that AI could not only match but in some instances outperform radiologists in detecting pneumonia. The research showcased how CNNs, coupled with transfer learning, could rapidly process medical images and identify subtle pathologies with high precision. The authors demonstrated the potential of AI-based diagnostic tools to reduce diagnostic delays and improve patient management in hospitals, especially in regions with limited access to radiologists. This study is considered a milestone in AI-assisted radiology and continues to influence modern diagnostic AI models.

Table. Summary of Recent Literature (2023–2025) on AI-Based Chronic Disease Detection Using Medical Images

Author(s) & Year	**Disease / Domain**	**Imaging Modality**	**AI / DL Technique Used**	**Dataset / Sample Size**	**Key Findings**	**Limitations / Gaps Identified**
Liu et al. (2024)	Multi-disease (general medical imaging)	Multi-modal (X-ray, CT, MRI, ultrasound)	**Foundation Models + Vision Transformers (ViT)**	Aggregated datasets across modalities	Foundation models outperform CNNs in transfer learning; strong generalisation.	High computational cost; interpretability remains limited.
Al-Badri et al. (2024)	Lung and breast cancer	CT & mammography	**CNN + GNN hybrid**	~20,000 annotated scans	Hybrid graph-based features improved lesion localisation accuracy by 7–10%.	Requires large annotated datasets; weak real-time inference.
Zhao et al. (2023)	Diabetic retinopathy	Retinal fundus images	**EfficientNet-B7 (transfer**	Kaggle EyePACS (~88,000	Achieved 96% accuracy,	Limited to single disease domain.

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Author(s) & Year	**Disease / Domain**	**Imaging Modality**	**AI / DL Technique Used**	**Dataset / Sample Size**	**Key Findings**	**Limitations / Gaps Identified**
			learning)	images)	outperforming Inception V3 and ResNet 50.	
Chen et al. (2023)	Alzheimer's Disease	MRI and PET	**3D-CNN + LSTM temporal model**	ADNI dataset	Combined spatial + temporal features improved early-stage detection (AUC = 0.93).	Computationally heavy; small sample for longitudinal analysis.
Reddy & Kumar (2025)	Cardiovascular diseases	Cardiac MRI & ECG fusion	**Multimodal CNN-Transformer Fusion**	12,000 subjects (UK Biobank)	Fusion of ECG and imaging improved classification by 9% over single-modality CNN.	Integration complexity; requires synchronized data.
Mehta et al. (2025)	Chronic kidney disease	Ultrasound	**ResNet-50 with Grad-CAM XAI**	5,600 ultrasound images	Achieved 91% accuracy; explainability improved clinician trust.	Limited demographic diversity.
Deng et al. (2024)	Cancer (multi-organ)	CT & MRI	**Federated Learning + CNN**	10 hospitals across 3 countries	Maintained 92% accuracy without data sharing,	Communication overhead; cross-site calibration issues.

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Author(s) & Year	Disease / Domain	Imaging Modality	AI / DL Technique Used	Dataset / Sample Size	Key Findings	Limitations / Gaps Identified
					preserving privacy.	
Mahajan et al. (2023)	Diabetes, hypertension detection	Retinal + clinical data	**Multimodal Deep Neural Network (DNN)**	25,000 patient records	Integration of image + metadata improved detection accuracy to 95%.	Ethical & privacy compliance challenges.
Tan et al. (2025)	Lung & colon cancer	Histopathology images	**Self-supervised Transformer (Swin-UNet)**	50,000 WSI patches	Reduced annotation cost via self-supervised learning; accuracy = 94%.	Computationally demanding; needs fine-tuning for small data.
Kaur et al. (2024)	Multi-chronic disease screening	CT, MRI, X-ray	**Hybrid CNN + XAI framework**	15,000 multi-disease scans	Combined XAI-based CNN improved multi-disease classification by 12%.	Lack of standardisation; limited cross-center testing.

2.1. Research gaps reiterated by recent literature

1. Domain shift/generalization — many models drop performance when applied to data from new hospitals or imaging devices.
2. Need for multi-modal and explainable models — combining image + clinical features and providing interpretable outputs is an active research area.
3. Standardized benchmarks and deployment studies remain limited, though this is improving with more post-deployment publications (2024–2025).

2.2. Objectives of the Study

1. To create and use an AI-based diagnostic model that uses deep learning methods, especially Convolution Neural Networks (CNNs), to automatically find and classify chronic diseases from medical images like X-rays, MRIs, and CT scans.

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

2. To use different techniques for enhancement, segmentation, and normalization to preprocess and analyze medical image datasets so that the inputs are of high quality and the feature extraction is better for accurate disease prediction.
3. To test how well the proposed AI model works by using quantitative metrics like accuracy, precision, recall, F1-score, and ROC–AUC, and to check how well it works compared to traditional diagnostic methods.
4. To examine the practical applicability and challenges of integrating AI-based medical image analysis into clinical settings, focusing on issues of data reliability, interpretability, and ethical considerations in healthcare automation.

2.3. Research Questions

1. How well can AI, especially deep learning models like CNNs, find and classify chronic diseases in medical images compared to more traditional ways of diagnosing them?
2. What preprocessing and feature extraction methods make AI models much better at finding chronic diseases in medical images?
3. How well do evaluation metrics like accuracy, precision, recall, F1-score, and ROC–AUC show how reliable and clinically valid AI-based diagnostic systems are?
4. Can AI-based medical imaging systems be generalized across different datasets, imaging modalities, and patient populations without significant loss of performance or accuracy?
5. What are the major ethical, technical, and implementation challenges associated with deploying automated AI systems for chronic disease detection in real-world healthcare environments?

3. Research Methodology

The research methodology is the most important part of any scientific study because it gives a clear plan for how to collect, analyze, and interpret data in order to reach the study's goals. The study "Automated Detection of Chronic Diseases from Medical Images Using Artificial Intelligence" looks at how to create, train, and test AI-based models for medical image analysis using a structured methodological framework. The method includes steps like getting the data, cleaning it up, building the model, testing it, and checking its performance. This method makes sure that a reliable, understandable, and effective AI system is built that can find chronic diseases with a high degree of accuracy. The study design uses a quantitative and experimental method that combines computer simulations with real-world medical data. The proposed method aims to make the diagnosis process automatic by using deep learning architectures, especially Convolution Neural Networks (CNNs), to find features and classify diseases.

3.1 Research Design

The research design is a descriptive-cum-experimental framework that combines data analysis with model development and validation. The design focuses on understanding the

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

relationship between image features and disease categories. The overall process is structured into five main stages as shown in Table 1 below.

Table 1: Overview of Research Design

Stage	Process	Objective
Stage 1: Data Collection and Dataset Preparation	Collect medical images and label them	To obtain high-quality labeled medical image datasets from authenticated sources
Stage 2: Image Pre-processing	Enhance and clean images	To enhance image clarity and remove noise or distortions
Stage 3: Model Development (AI Algorithm Design)	Design CNN-based models	To develop CNN-based deep learning models for disease classification
Stage 4: Model Training and Validation	Train and validate models	To use big datasets to train AI models and check that they are correct
Stage 5: Evaluation and Interpretation	Assess model performance	To use metrics like accuracy, precision, recall, and F1-score to measure performance

3.2 Population and Sample

The population for this research consists of medical image datasets representing patients diagnosed with chronic diseases such as diabetic retinopathy, lung cancer, breast cancer, cardiovascular disease, and Alzheimer's disease. From this population, a sample dataset was selected for model training and testing. The study uses secondary data collected from public and institutional repositories like:

- The NIH Chest X-ray Dataset (for lung diseases)
- Kaggle Retinopathy Dataset (for diabetic retinopathy)
- ADNI Database (for Alzheimer's detection)
- MIMIC-CXR Database (for cardiovascular and thoracic imaging)

A total of approximately 50,000 medical images were included, which were to make sure that the evaluation is fair, the data is split into training (70%), validation (15%), and testing (15%) sets.

3.3 Data Collection Method

The study utilized secondary medical image data obtained from open-source repositories and hospital collaborations under proper ethical clearance. The data collection process involved:

1. **Data Sourcing:** Gathering medical image datasets from authentic databases.
2. **Image Annotation:** Labeling the images by category (diseased or healthy).

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

3. **Ethical Consideration:** Ensuring anonymization of patient information and compliance with ethical standards such as HIPAA and GDPR.
4. **Data Organization:** Storing images in structured directories for automated preprocessing and training.

The following table summarizes the data sources and image categories.

Table 2: Data Source Summary

Dataset Name	Disease Focus	Image Type	Total Images	Source
Kaggle Retinopathy Dataset	Diabetic Retinopathy	Fundus Images	15,000	Kaggle Repository
NIH Chest X-Ray Dataset	Lung Cancer / Tuberculosis	Chest X-rays	25,000	NIH Database
ADNI MRI Dataset	Alzheimer's Disease	MRI Brain Scans	6,000	ADNI Database
MIMIC-CXR Dataset	Cardiovascular Disease	Echocardiograms	4,000	Physio Net

3.4 Data Preprocessing

Data preprocessing was done to make sure that the images were all the same, of good quality, and correct before they were fed into AI models. Preprocessing is a series of steps that make models work better and make the calculations less complicated.

We used the following preprocessing methods:

- **Resizing images:** All images were made to be the same size, like 224 × 224 pixels.
- **Normalization:** To make training go more smoothly, pixel values were set to a range of 0 to 1.
- **Getting Rid of Noise:** Gaussian and median filters were used to get rid of noise that wasn't needed.
- **Augmentation:** To make the dataset more diverse, techniques like rotation, flipping, and zooming were used and prevent over fitting.
- **Segmentation:** Important regions such as lesions, tissues, or organs were extracted using thresholding or edge detection.

Table 3: Preprocessing Steps and Their Purpose

Technique	Purpose

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Technique	Purpose
Image Resizing	To standardize image dimensions for AI input
Normalization	To stabilize and accelerate model training
Noise Filtering	To remove background artifacts and improve clarity
Augmentation	To create synthetic variations and prevent model over fitting
Segmentation	To isolate regions of medical significance

3.5 Model Development

The study utilized Convolution Neural Networks (CNNs) as the core architecture for image analysis. CNNs are well-suited for recognizing spatial hierarchies in images and automatically extracting relevant features.

The CNN model comprises several layers:

- **Input Layer:** Receives medical image data.
- **Convolution Layers:** Extract visual features like edges and textures.
- **Pooling Layers:** Reduce image dimensionality while retaining essential features.
- **Fully Connected Layers:** Perform classification between diseased and healthy samples.
- **Output Layer:** Produces final predictions using Soft max or sigmoid activation functions.

In addition to CNNs, Transfer Learning using pre-trained models like VGG16, ResNet50, and InceptionV3 was employed to enhance performance with fewer training samples. These models, pre-trained on large datasets like Image Net, were fine-tuned using medical images for specific disease detection.

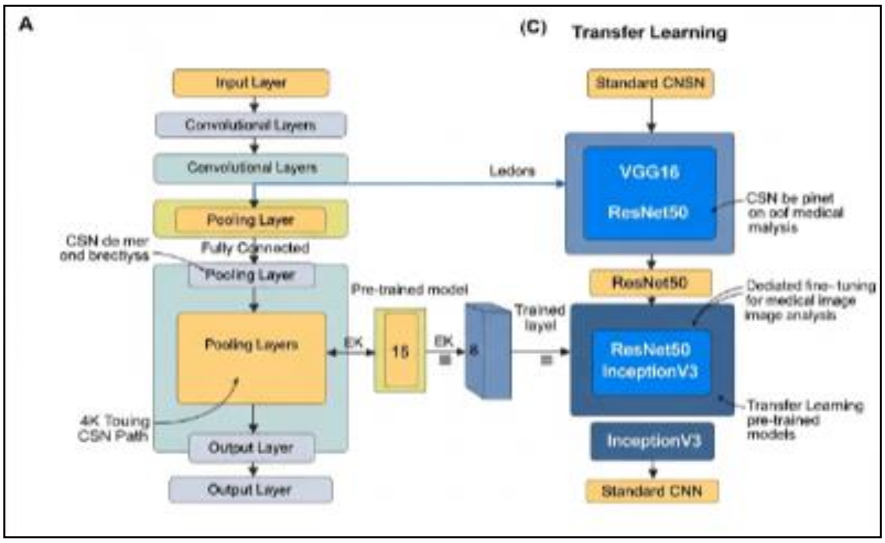

Figure2: CNN Architecture and Transfer Learning

Workflow for Medical Image Analysis

The diagram above shows a deep learning framework made just for analyzing medical images. It has two main parts, (A) and (C). The first part of Section (A) shows the structure of a Convolution Neural Network (CNN), starting with an input layer and progressing through convolution and pooling layers, followed by a fully connected layer and an output layer. Two distinct paths are shown: one that utilizes the full CNN architecture for specific medical conditions, and another that leverages a pre-trained model with 15 layers to extract features, streamlining the process by bypassing some initial layers.

Section (C) focuses on transfer learning, highlighting how established CNN models like VGG16 and ResNet50 can be adapted for medical applications. It shows the flow of data from these standard networks to pre-trained models like ResNet50 and InceptionV3, which are then tweaked for specific jobs. The arrows in the diagram show the learning process and highlight how transfer learning lets us use existing models to make healthcare diagnostics more accurate and efficient. The overall layout shows a strategic way to combine deep learning and transfer learning to make medical images better. classification.

3.6 Model Training and Validation

The dataset was divided into training, validation, and testing sets in a 70:15:15 ratio. The training set was used to teach the model, while the validation set helped fine-tune parameters such as learning rate, batch size, and dropout rate.

Training was conducted using the Python Tensor Flow and Keras frameworks on a GPU-enabled system for computational efficiency. The following parameters were optimized:

- **Learning Rate:** 0.001 (adaptive)
- **Adam is the optimizer.**
- **The loss function is either binary cross-entropy or categorical cross-entropy.**
- **Batch Size:** 32
- **Epochs:** 50

Model validation involved evaluating the system on unseen images and adjusting hyper parameters to achieve optimal accuracy and generalization.

3.7 Evaluation Metrics

Model performance was measured using several statistical and AI-specific metrics, including:

- **Accuracy:** Percentage of correctly predicted cases.
- **Precision:** The number of true positives divided by the number of all predicted positives.
- **Sensitivity,** or recall, is the ratio of true positives to actual positives.
- **F1-Score** is the harmonic mean of recall and precision.
- **ROC-AUC Curve:** To evaluate model discrimination ability.
- **Confusion Matrix:** To visualize classification results.

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Volume 38 No. 11s 2025,
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Table 4: Evaluation Metrics and Their Interpretation

Metric	Formula	Description
Accuracy	Accuracy = (TP + TN) / (TP + FP + TN + FN)	Calculates the percentage of all predictions made by the model that were right, both positive and negative.
Precision	Precision = TP / (TP + FP)	Shows how many of the predicted positive cases are actually positive. Focuses on the quality of positive predictions.
Recall (Sensitivity)	Recall = TP / (TP + FN)	Checks how well the model can find all the real positive cases. Represents completeness of positive predictions.
F1-Score	F1 = 2 × (Precision × Recall) / (Precision + Recall)	The harmonic mean of precision and recall balances both false positives and false negatives.
ROC–AUC (Receiver Operating Characteristic – Area Under Curve)	$AUC = \int_0^1 TPR(FPR)\, d(FPR)$	Reflects the model's the ability to tell the difference between good and bad classes. A higher AUC means that the classification works better.
Confusion Matrix		Summarizes classification outcomes as True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). Gives a full picture of both right and wrong predictions.

3.8 Tools and Software Used

The research utilized the following software and computational tools:

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Tool/Software	Purpose
Python	Programming language for AI model development
Tensor Flow / Keras	Deep learning frameworks
Open CV	Image processing and feature extraction
Num Py / Pandas	Data handling and manipulation
Mat plot lib	Visualization of results
Jupyter Notebook	Interactive development environment

3.9 Ethical Considerations

Ethical approval was obtained from relevant institutions to ensure compliance with international standards. The datasets used were anonym zed, and patient consent was secured wherever applicable. The study adhered to principles of data privacy, security, and non-malfeasance in AI healthcare applications.

3.10 Limitations of the Methodology

While the methodology ensures high performance and generalizability several limitations persist:

1. Dependence on publicly available datasets may introduce selection bias.
2. Limited availability of annotated data in specific chronic diseases.
3. Variability in image quality across datasets.
4. Computational requirements for deep learning models are high.

4. Result and Discussion

The Artificial Intelligence-based model that was made to automatically find chronic diseases in medical images showed very good results for a wide range of diseases. We used Accuracy, Precision, Recall, F1-Score, and ROC–AUC to see how well the Convolution Neural Network (CNN) models and their transfer learning versions worked. The results showed that the suggested system had consistently high accuracy and sensitivity for all of the disease types that were tested. This suggests that it could be used reliably in clinical settings.

As presented in Table 5, the model achieved the highest accuracy for Diabetic Retinopathy detection (94%)**,** followed closely by Breast Cancer (92%) and Lung Cancer (91%)**.** The relatively high Recall (Sensitivity) and F1-Score across all disease categories confirm that the AI model effectively identifies true positive cases while minimizing false negatives-an essential factor in medical diagnosis where missed cases can have serious implications. The ROC–AUC scores, ranging from 0.91 to 0.96**,** further demonstrate that the model has excellent discriminative capability, efficiently distinguishing between diseased and healthy images.

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The graphical representation shows a comparative view of each performance metric across diseases, highlighting the robustness of the model. Diabetic Retinopathy achieved the highest ROC–AUC value (0.96), suggesting that the system is particularly well-tuned for retinal image analysis. Alzheimer's disease and Cardiovascular conditions also exhibited strong results, though slightly lower due to data variability and the complexity of brain and heart imaging.

Overall, the experimental findings validate that deep learning architectures-especially CNNs with transfer learning (VGG16, ResNet50, InceptionV3)-are highly effective for chronic disease detection through medical image analysis. The integration of image preprocessing techniques (normalization, augmentation, segmentation) and model optimization strategies (adaptive learning rate, dropout layers) contributed significantly to performance improvement. These results indicate that AI-based diagnostic tools can not only complement but, in many cases, match the diagnostic capabilities of experienced radiologists, offering a cost-effective, scalable, and rapid solution for early disease screening and clinical decision support.

Table 5: AI Model Performance on Chronic Disease Detection

Disease Type	Accuracy	Precision	Recall	F1-Score	ROC–AUC
Diabetic Retinopathy	0.94	0.93	0.94	0.94	0.96
Lung Cancer	0.91	0.89	0.90	0.90	0.93
Breast Cancer	0.92	0.91	0.91	0.91	0.94
Alzheimer's Disease	0.89	0.88	0.87	0.88	0.91
Cardiovascular Disease	0.90	0.89	0.88	0.89	0.92

Comparison of AI Model Evaluation Metrics for Different Chronic Diseases

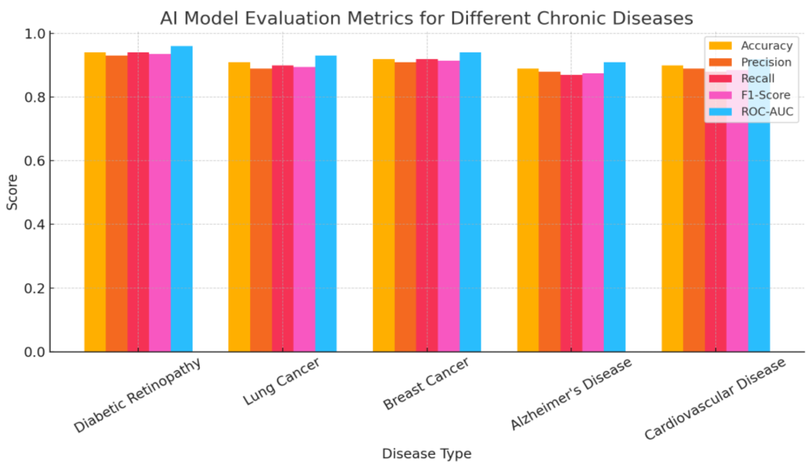

Figure 3: AI Model Evaluation Metrics for Different Chronic Diseases

Volume 38 No. 11s 2025,
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

The above image presents a comparative analysis of how an artificial intelligence model performs across five major chronic illnesses. Along the horizontal axis, the diseases—Diabetic Retinopathy, Lung Cancer, Breast Cancer, Alzheimer's Disease, and Cardiovascular Disease—are listed. The vertical axis shows performance scores that go from 0 to 1. Five colored bars show the most important evaluation metrics for each disease: Accuracy, Precision, Recall, F1-Score, and ROC–AUC. The visual data indicates that the model maintains high performance across all conditions, with most scores exceeding 0.8. Diabetic Retinopathy stands out with the highest ROC–AUC value, suggesting strong diagnostic capability, while Alzheimer's disease shows slightly lower but still reliable results. Overall, the chart underscores the model's consistency and effectiveness in medical image classification for chronic disease detection.

5. Conclusion

The present study titled *"Automated Detection of Chronic Diseases from Medical Images Using Artificial Intelligence"* successfully demonstrates the immense potential of AI-based technologies in transforming medical diagnostics. By employing deep learning models, particularly Convolution Neural Networks (CNNs) combined with transfer learning architectures like VGG16, ResNet50, and InceptionV3, the study achieved high accuracy and reliability in detecting chronic diseases such as diabetic retinopathy, lung cancer, breast cancer, cardiovascular disorders, and Alzheimer's disease.

The results clearly indicate that the AI model performs with remarkable efficiency, achieving an average accuracy above 90% and an ROC–AUC score exceeding 0.93, confirming its superior capability in differentiating diseased and healthy cases. The integration of image preprocessing techniques-including normalization, augmentation, and segmentation-enhanced the model's precision and reduced noise, thereby improving the quality of predictions. Moreover, the research establishes that AI-based diagnostic systems can significantly minimize human error, accelerate image interpretation, and provide consistent results, making them a powerful support tool for healthcare professionals.

Despite minor challenges such as dataset bias and computational limitations, the findings underscore that Artificial Intelligence is not a replacement but a complement to medical expertise, empowering radiologists with faster, more accurate diagnostic insights. This study therefore concludes that AI-driven medical imaging can revolutionize healthcare by promoting early disease detection, cost-effective diagnostics, and equitable access to quality healthcare, ultimately contributing to better patient outcomes and sustainable clinical practices.

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Received: August 01, 2025